Vienna, 13 April 2018

Barcelona Supercomputing Center
Centro Nacional de Supercomputación

EXCELENCIA SEVERO OCHOA

Sub-seasonal to seasonal forecasts from a climate service perspective

Francisco J. Doblas-Reyes

iCrea

The climate services scene

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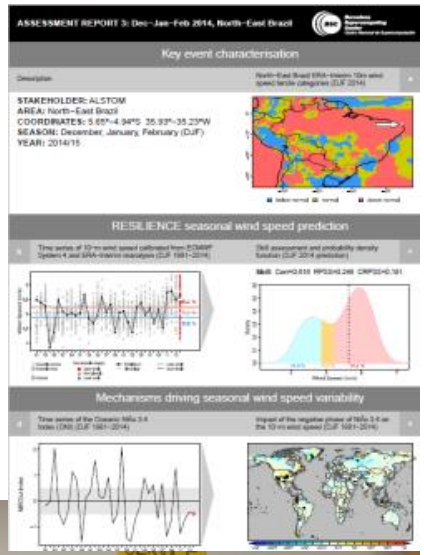
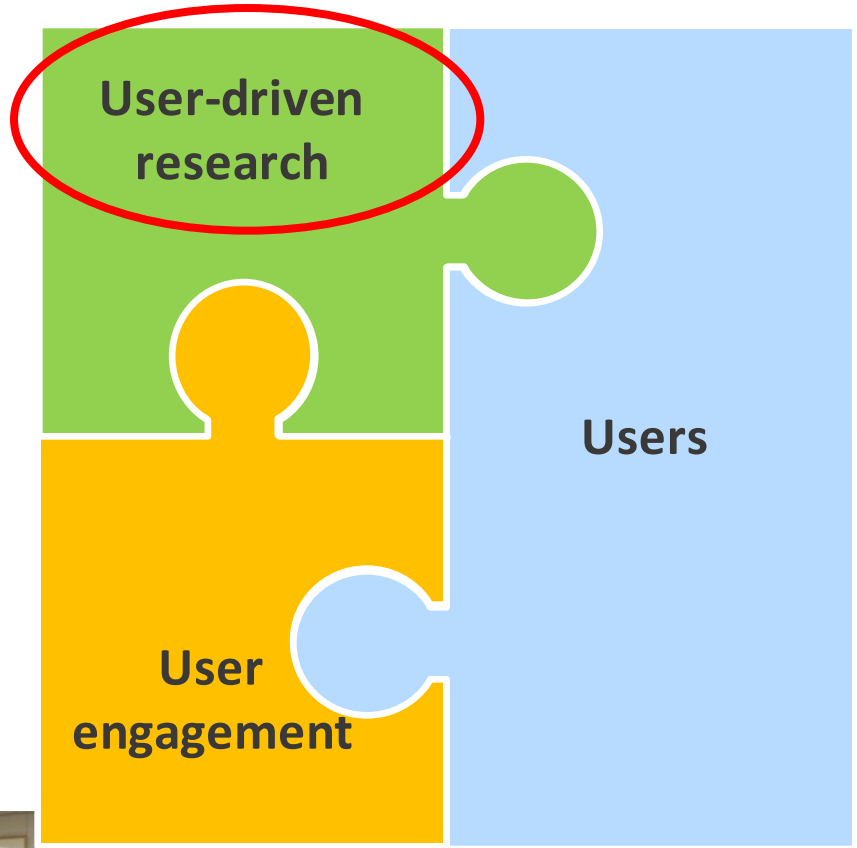
Case studies for specific needs

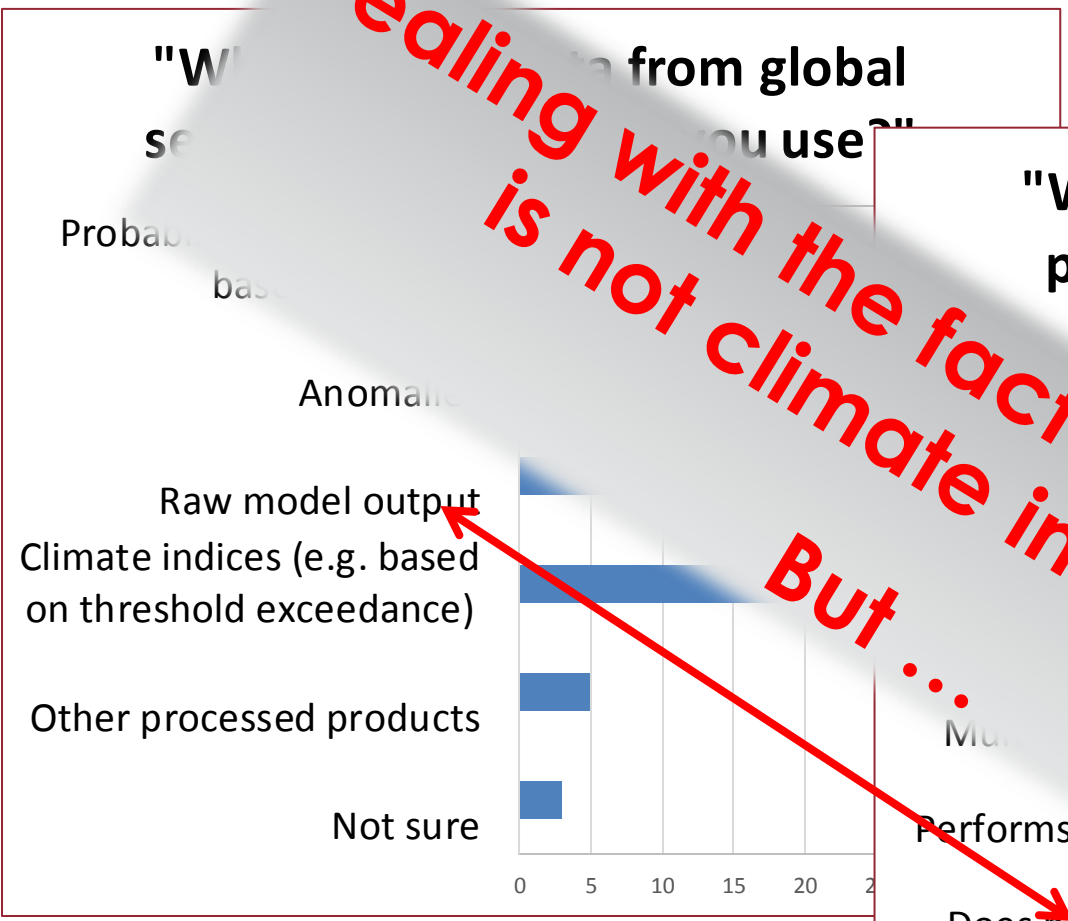


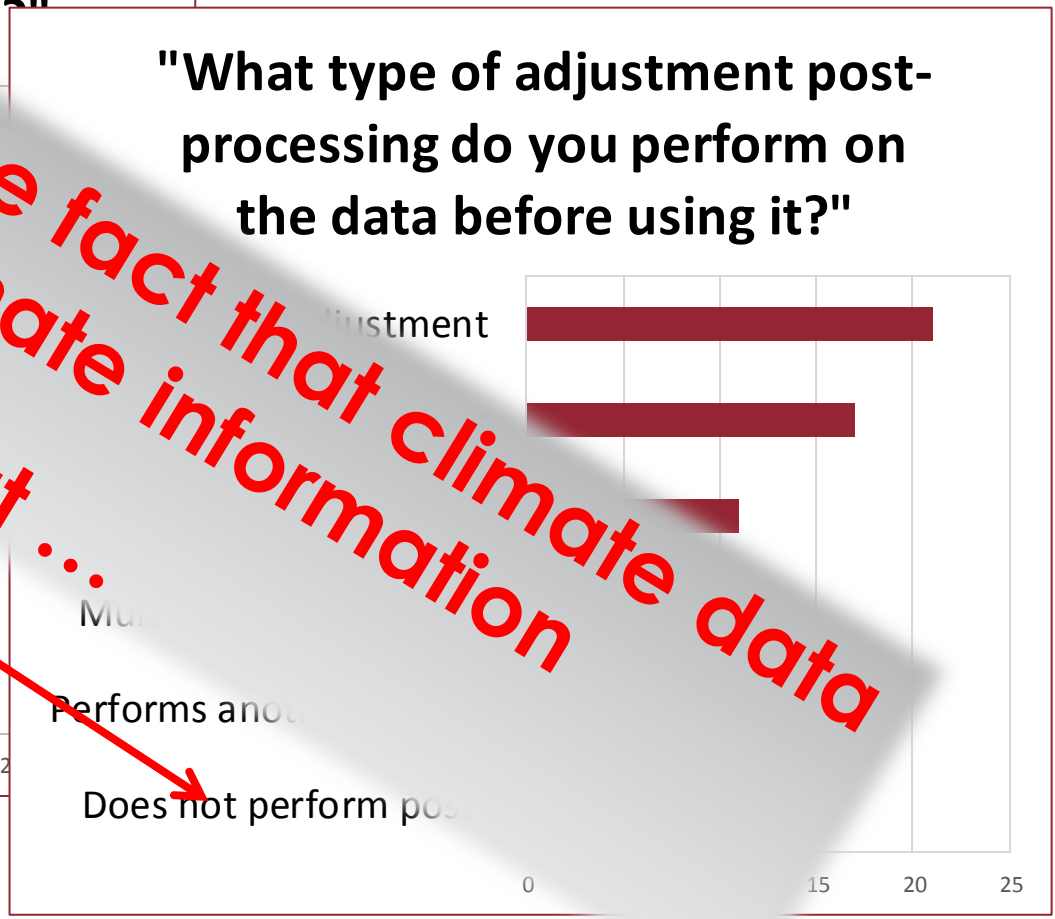


Participatory approaches

User engagement and consultation

Results from a user survey performed in the framework of the Copernicus Climate Change Service contract QA4Seas.



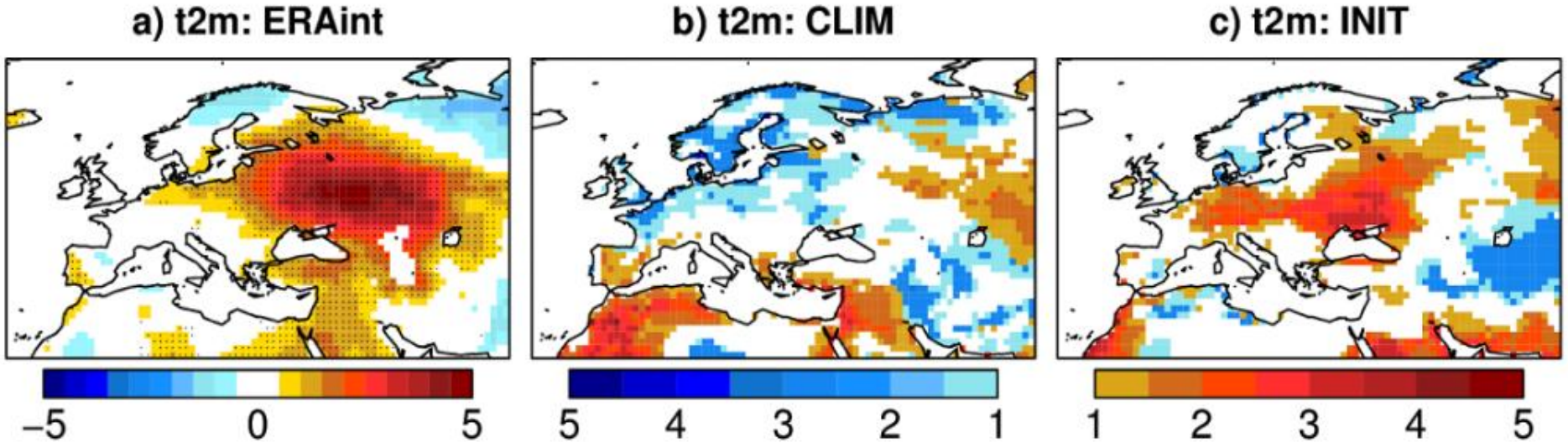


Dealing with the fact that climate data is not climate information

But …

Improving land initial conditions

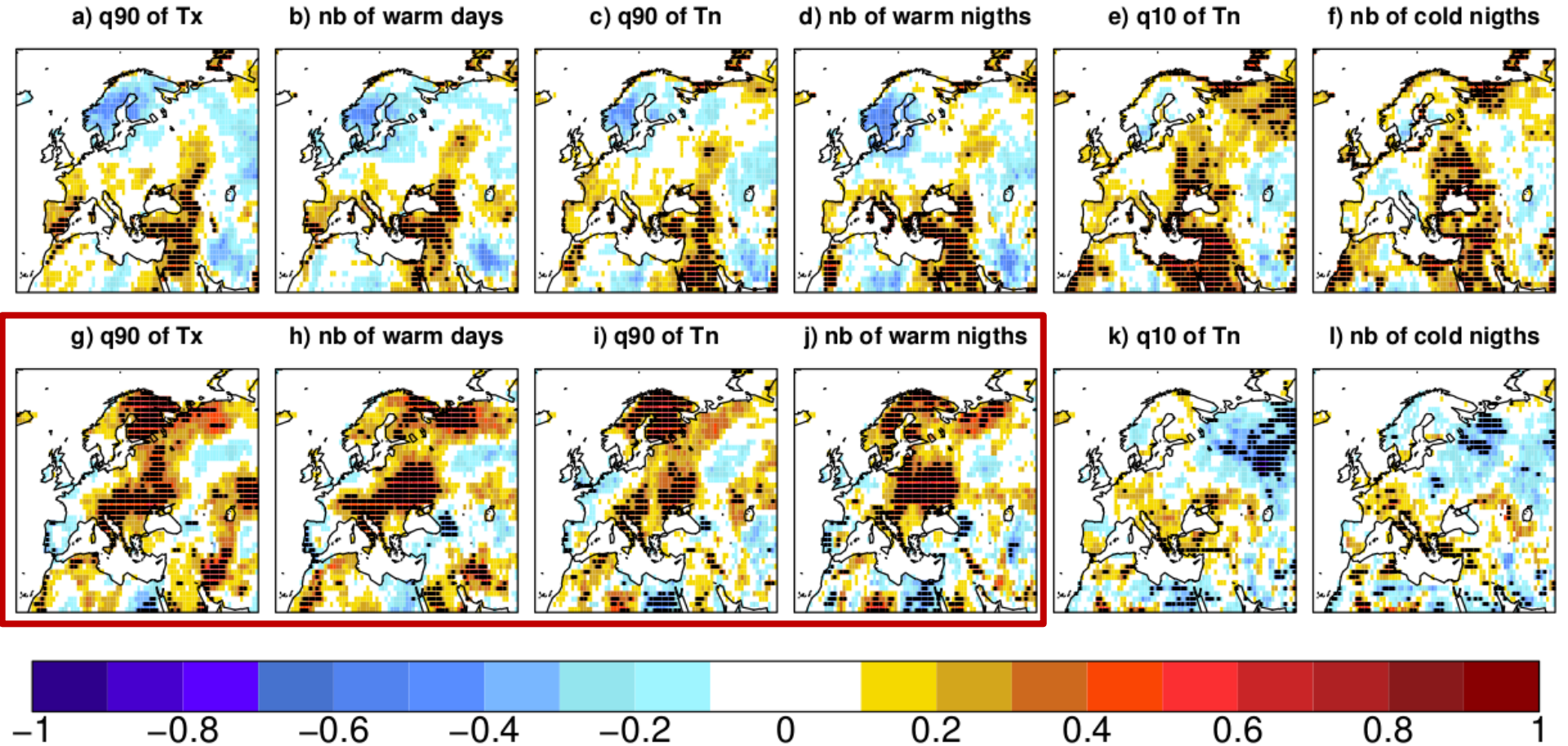
JJA near-surface temperature anomalies in 2010 from ERAInt (left) and odds ratio from experiments with a climatological (centre) and a realistic (right) land-surface initialisation for the upper quintile event. Results for EC-Earth2.3 started in May with initial conditions from ERAInt, ORAS4 and a sea-ice reconstruction over 1979-2010.



Prodhomme et al. (2015, Clim. Dyn.)

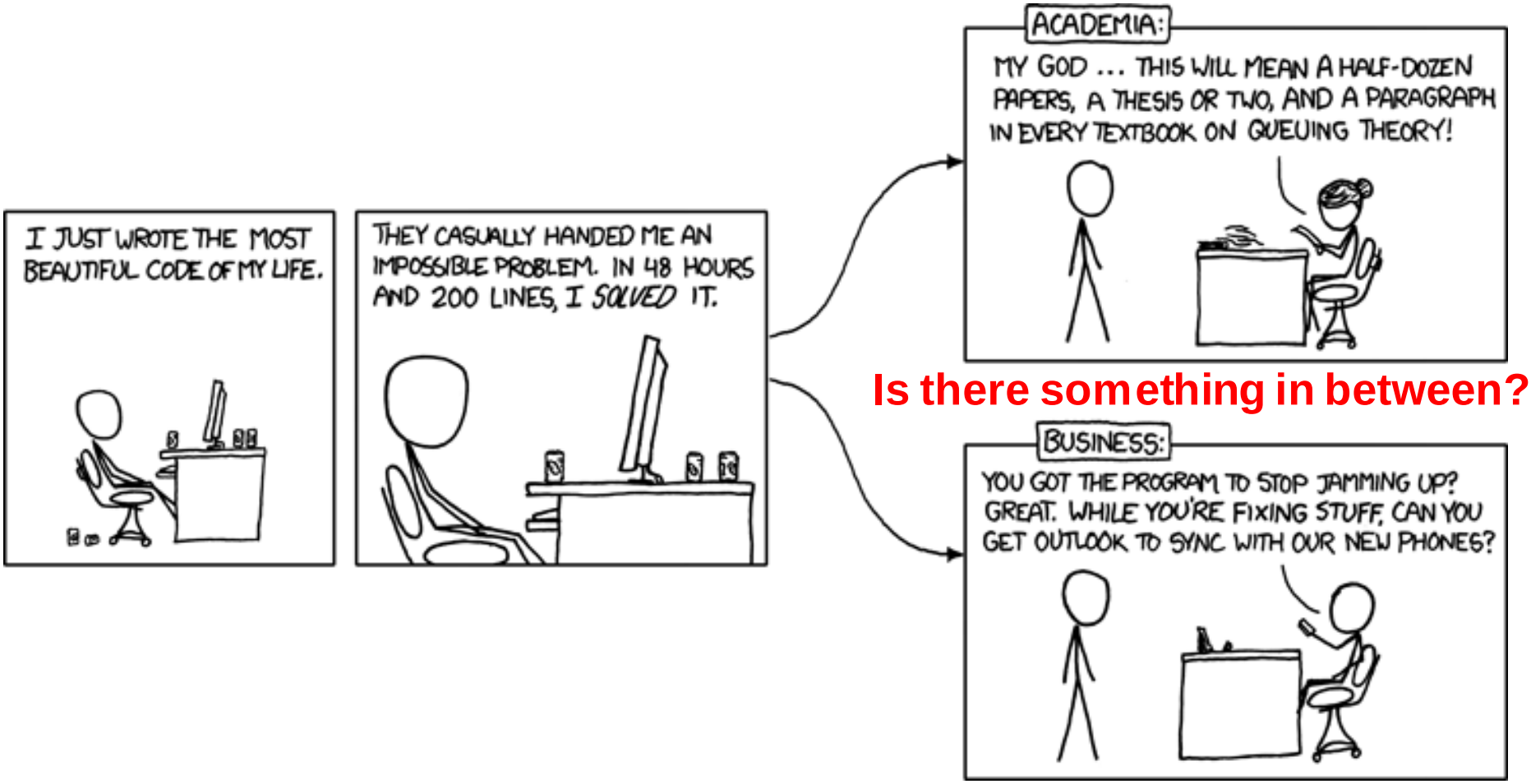
Improving land initial conditions

JJA near-surface temperature correlation of the ensemble mean from experiments with a climatological (top) and difference with one with realistic (bottom) land-surface initialisation. Results for EC-Earth2.3 started in May over 1979-2010.



Prodhomme et al. (2015, Clim. Dyn.)

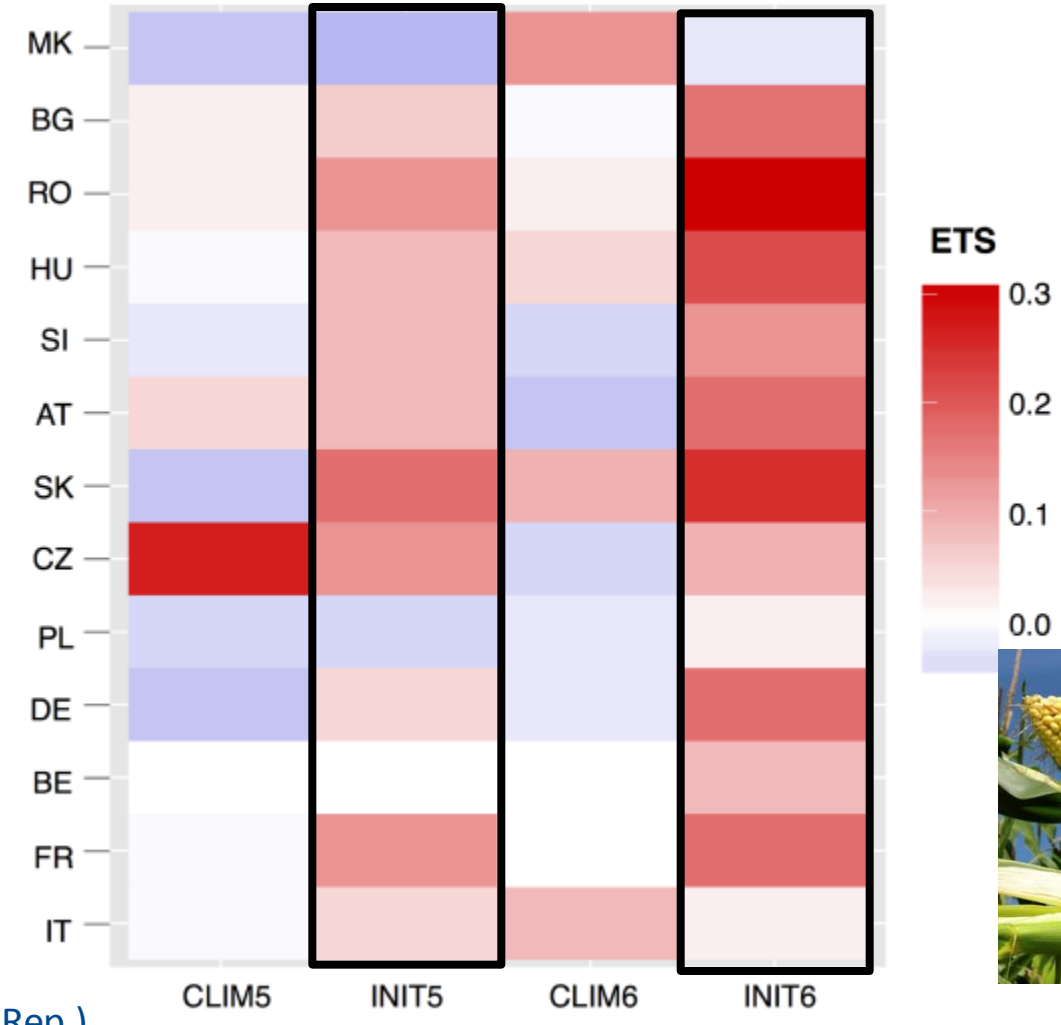
What for?



xkcd.com

Improved predictions for agriculture

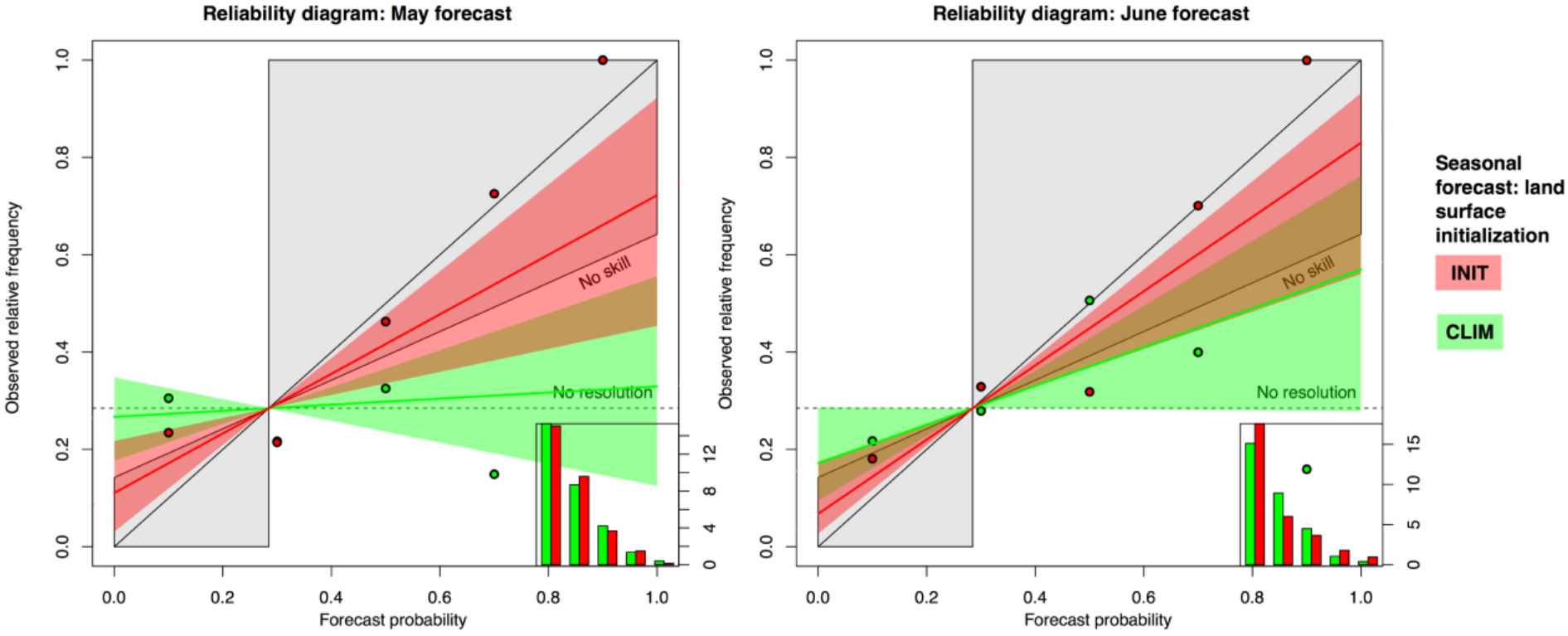
Equitable threat score (ETS) of predictions of poor maize yield (lower quartile) from EC-Earth when the land-surface uses realistic initial conditions (INIT) wrt conditions with no interannual information (CLIM).



Ceglar et al. (2018, Sci. Rep.)

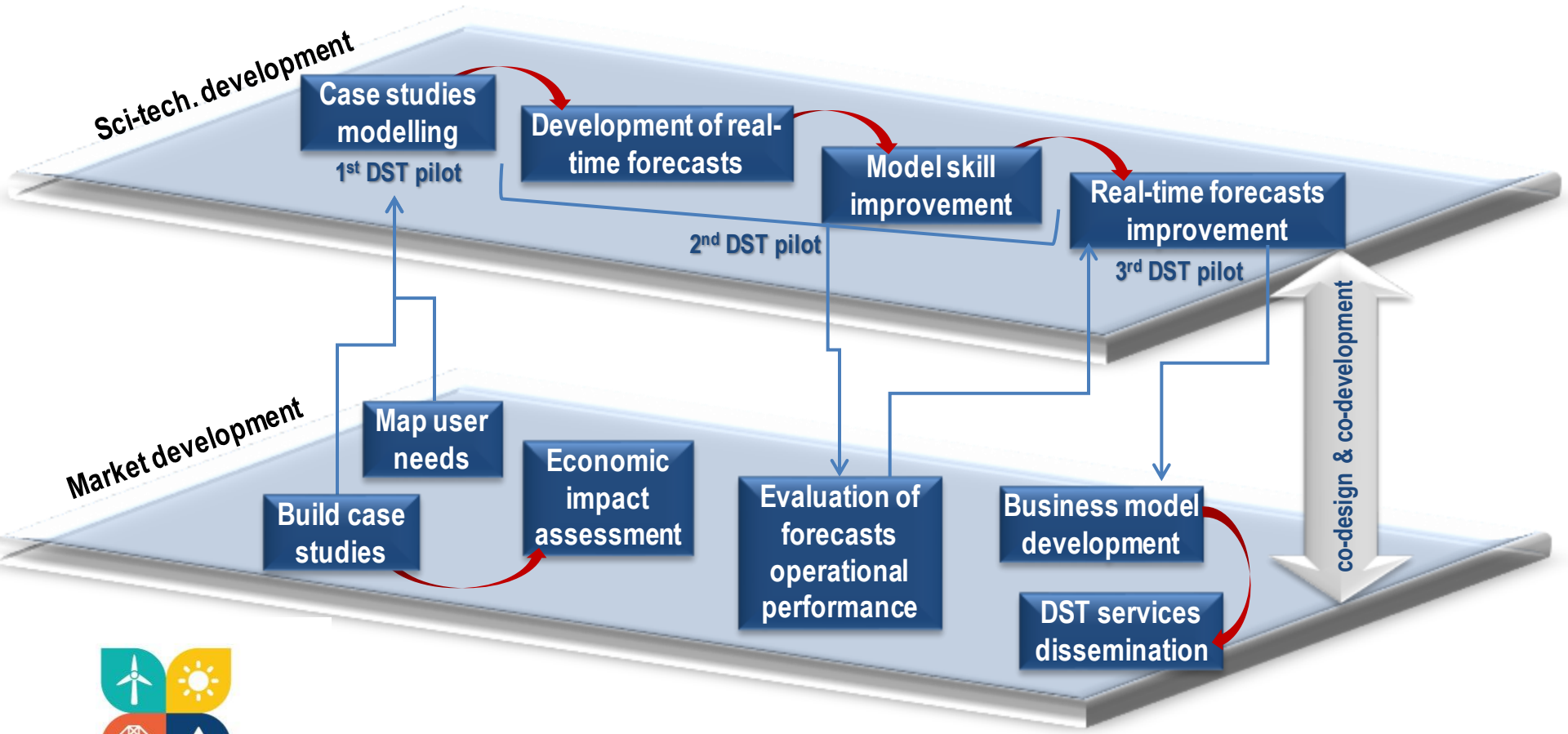
Improved predictions for agriculture

Reliability diagram of predictions of poor maize yield (lower quartile) from EC-Earth seasonal predictions when land-surface is initialised with realistic (INIT) and climatological (CLIM) initial conditions with May and June start dates.



Ceglar et al. (2018, Sci. Rep.)

Prototypical climate service for energy

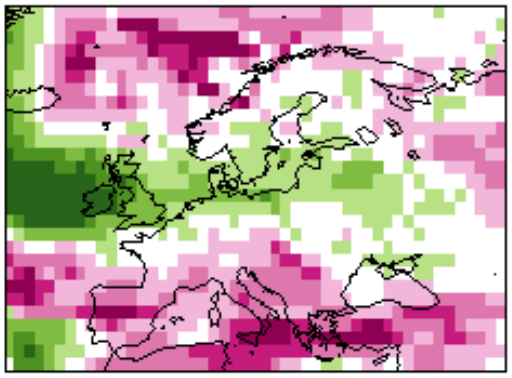


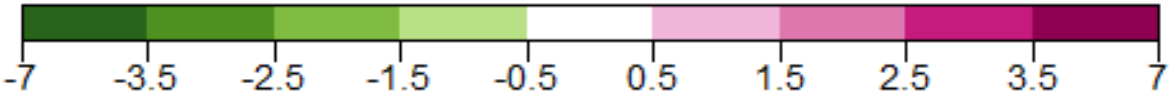
S2S4E
Climate Services for Clean Energy

Predictions for wind energy

10-metre wind speed for 2-8 February 2015 (m/s)

ERAI





V. Torralba (BSC)

Predictions for wind energy

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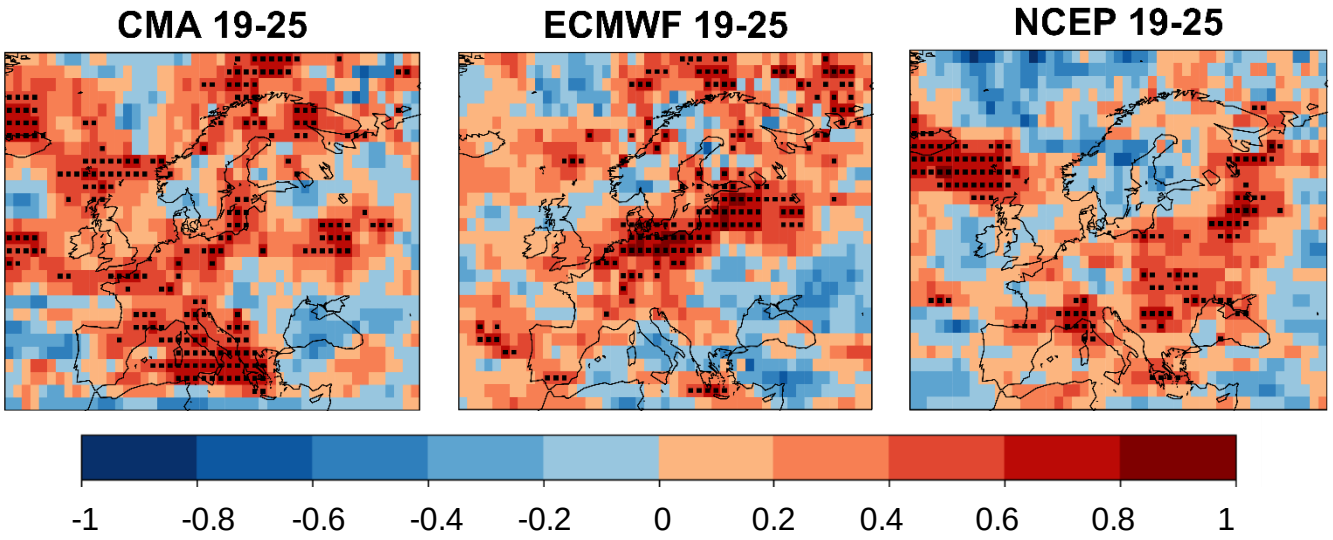
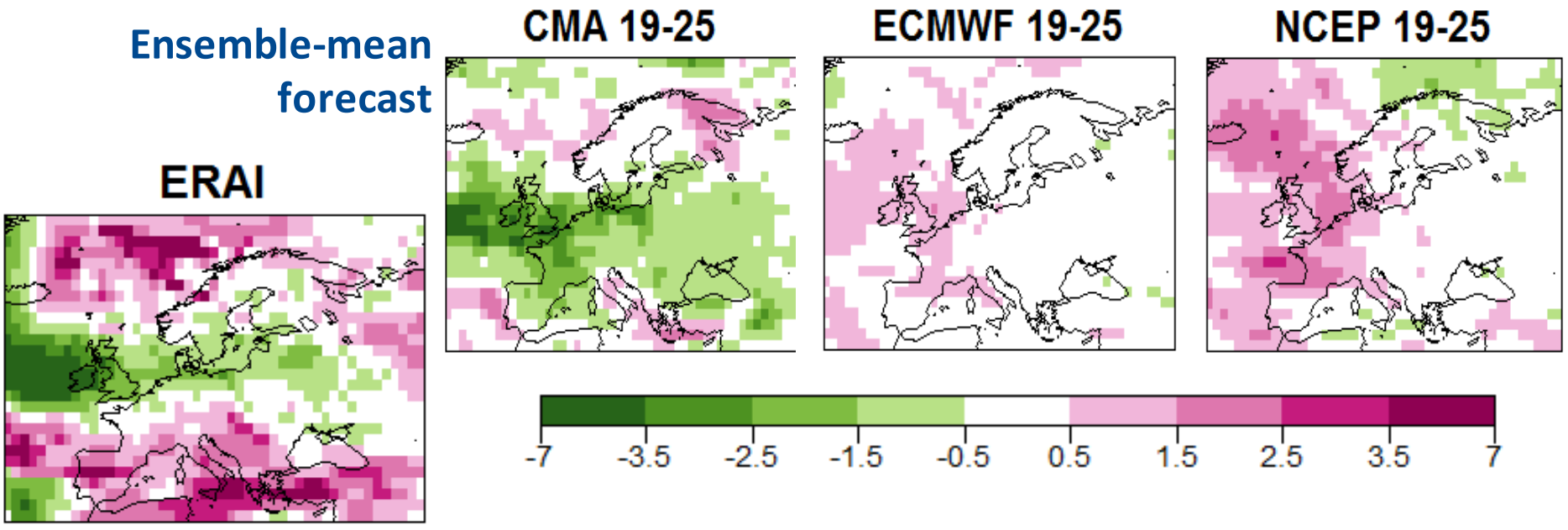
Ensemble-mean correlation (institution and forecast time)



Ensemble-mean forecast



Predictions for wind energy

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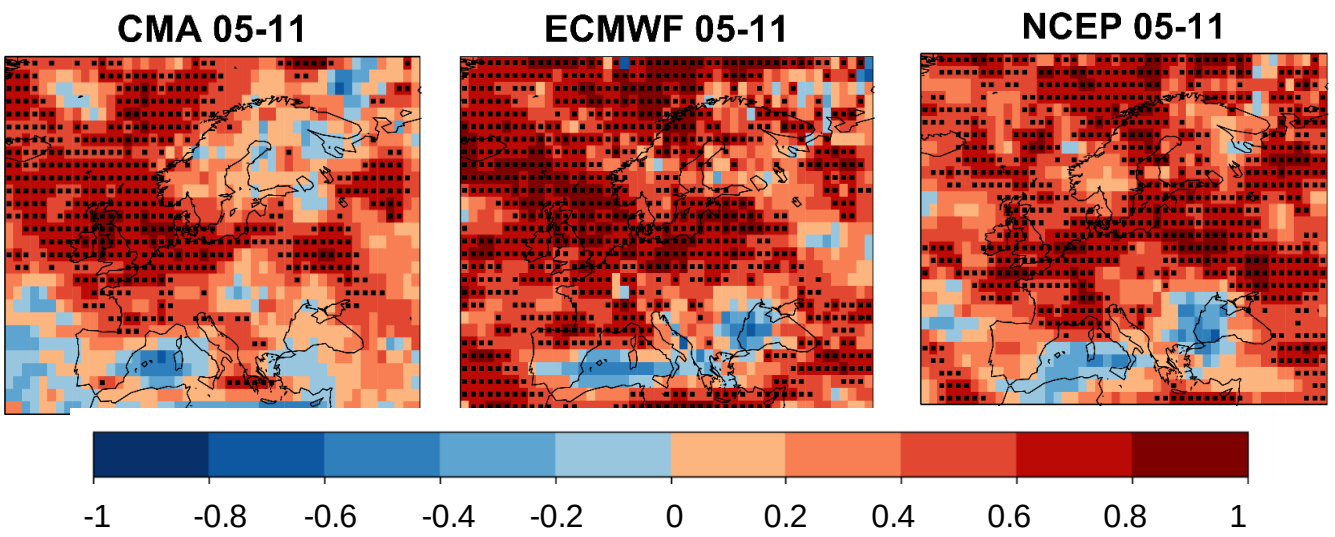
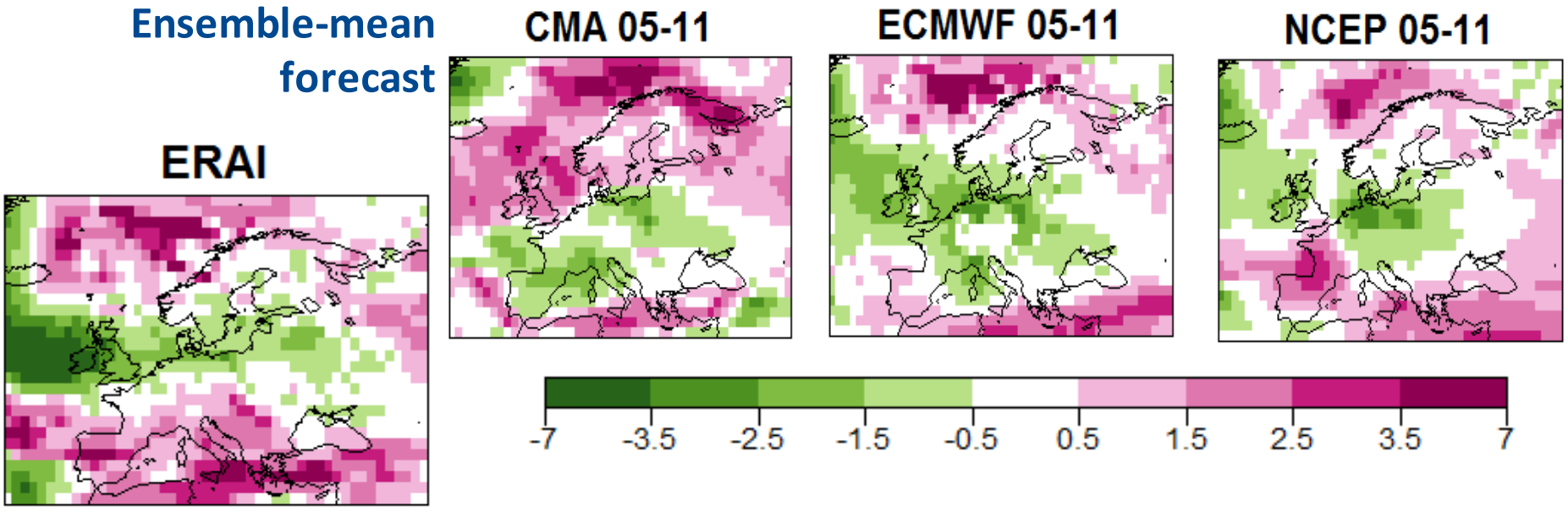
Ensemble-mean correlation (institution and forecast time)

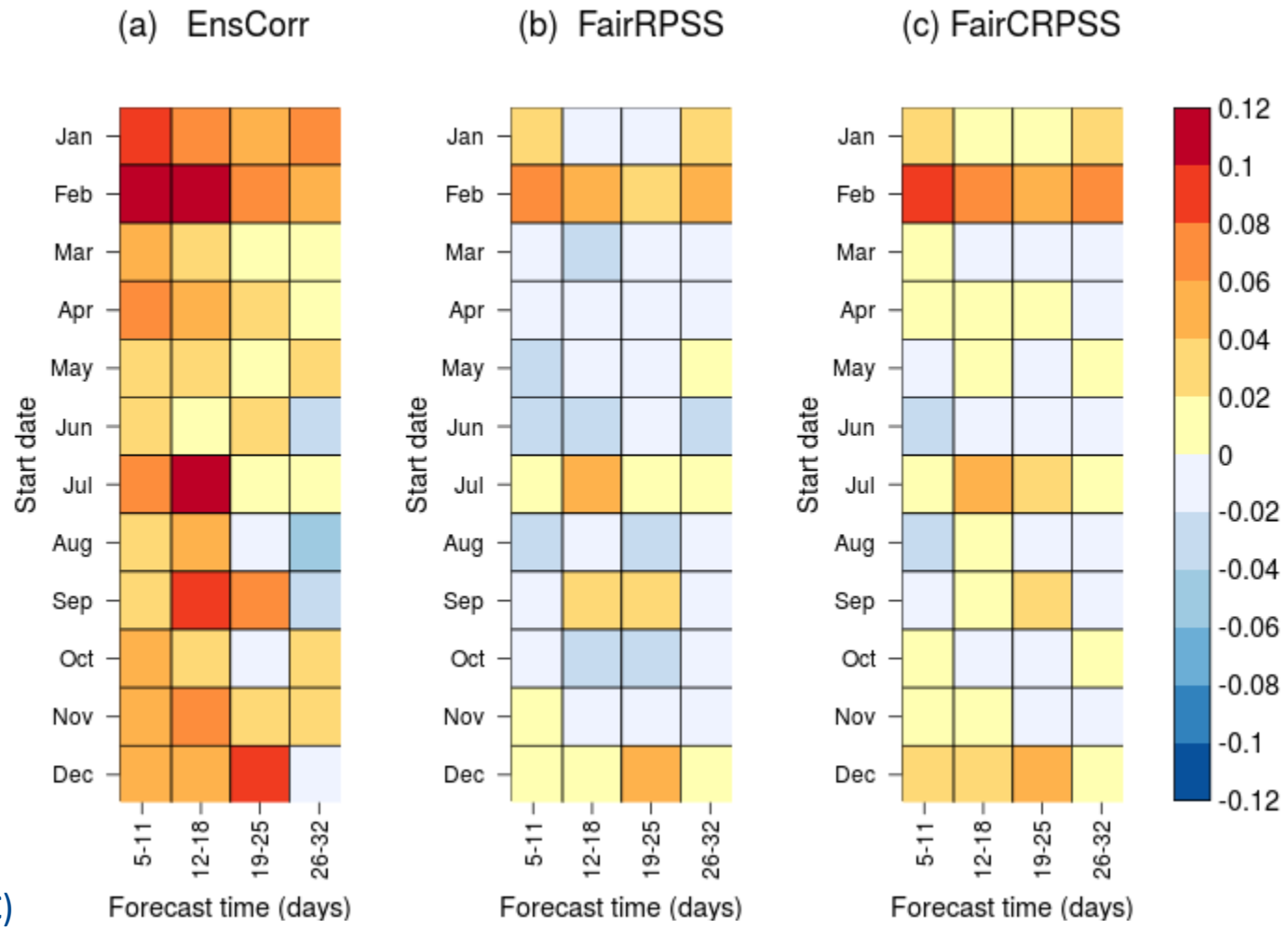


Ensemble-mean forecast



Improving wind predictions

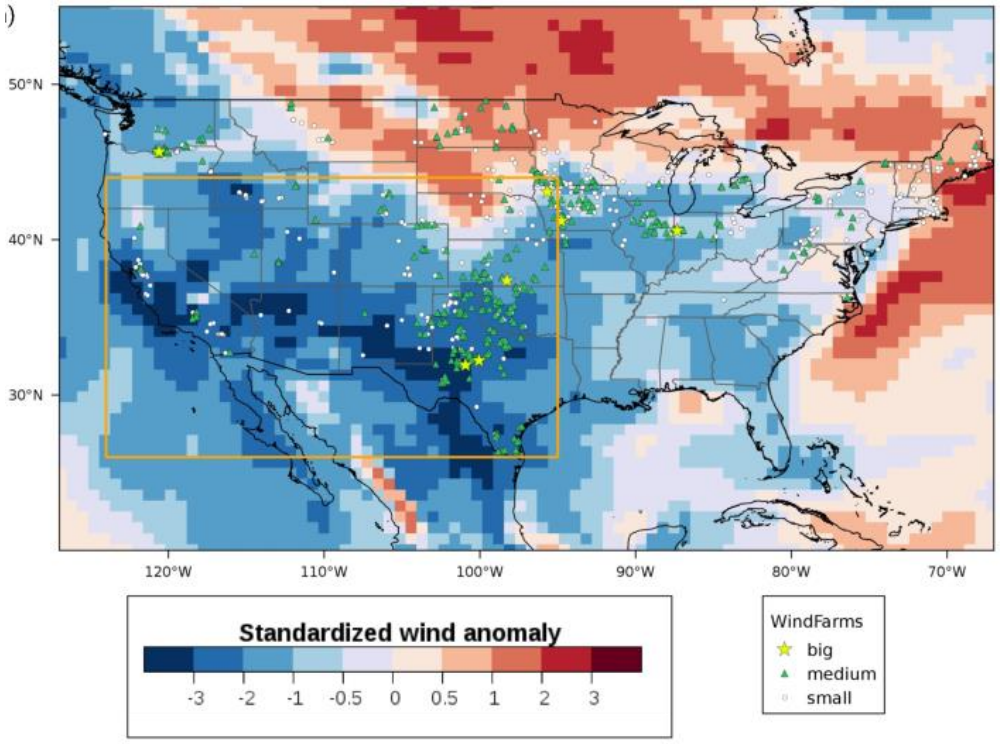
Forecast quality improvement in 10-metre wind speed of the ECMWF sub-seasonal forecast system between the CY43R3 and CY40R1 versions for the North Sea region over 1996-2013.

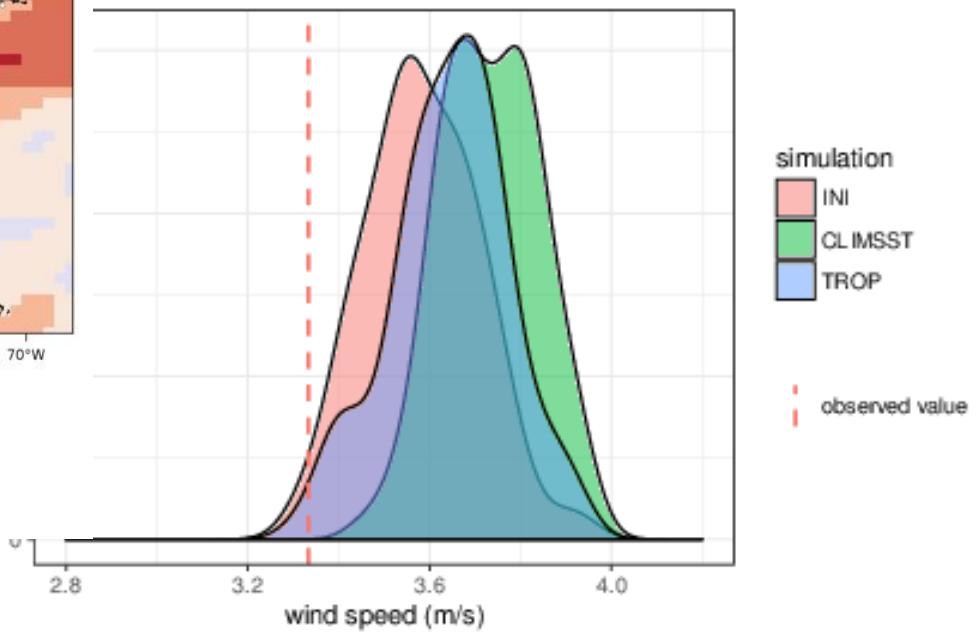


Through the looking glass

Attribution of the JFM 2015 wind drought over North America. Both west tropical and extratropical Pacific SSTs play a role in the wind drought.

Shouldn't have been for the wind energy managers' request, we'd never have looked into this issue.





Lledó et al. (2018, JGR)

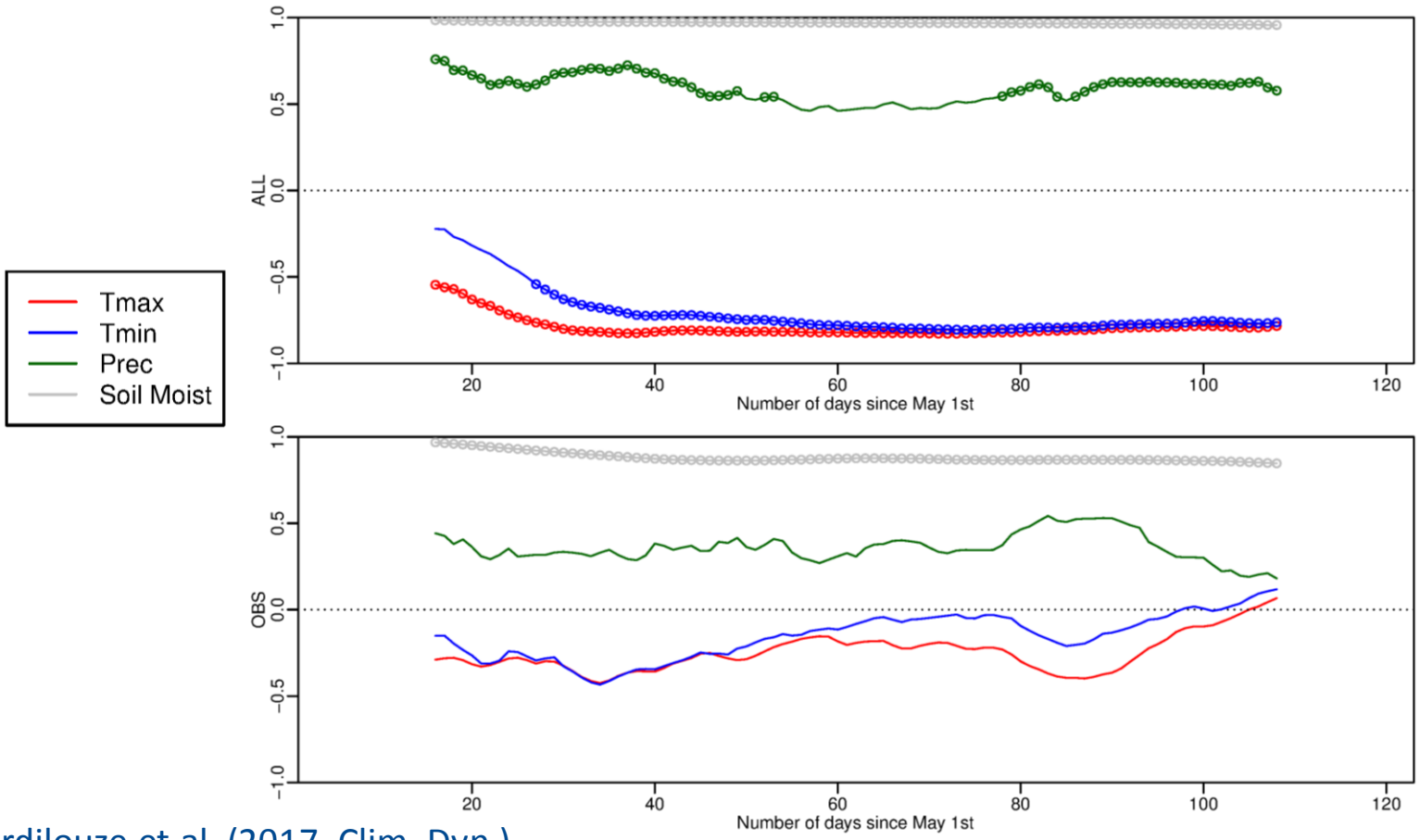
A new paradigm has come to stay: user-driven research

- **Progress**: opportunities for research and services to grow together, involve private sector in research for better systems.
- **Heterogeneity**: link to and merge our data with communities with larger impact (urban, arts, social).
- **Education**: in the era of open data, take advantage of the open education opportunities.
- **Standards**: in a collaborative environment standards are a must and everyone's (users and providers) responsibility.
- **Technology**: make the most of a rapidly evolving technology (heterogeneous hardware, software, mobile data capture, visualisation, computing and storage outsourcing).

Forecast drift prevents skill

Correlation between 1st of May total soil water content and 31-day running mean of variables from the SPECS multi-model seasonal forecast (top) and ERAInt (bottom) over North American Great Plains.

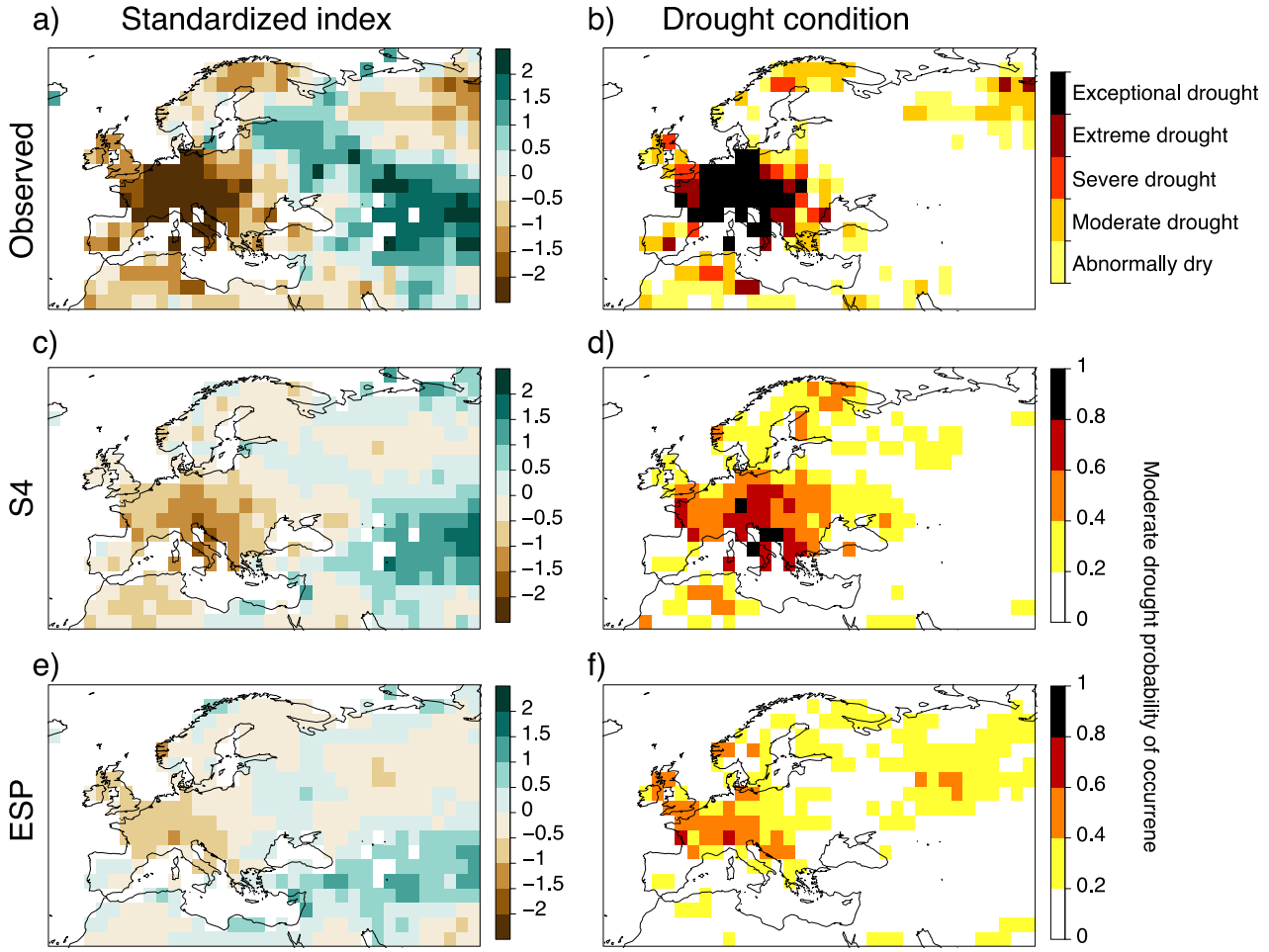
The model shifts quickly to excessive land-atmosphere coupling.



Ardilouze et al. (2017, Clim. Dyn.)

Drought predictions

(Left) Six-month SPEI and (right) observed drought condition for August 2003 as observed, from ECMWF System 4 and from an ensemble streamflow prediction (ESP, from resampled historical data).



Turco et al. (2017, ERL)

Improved predictions for wind energy

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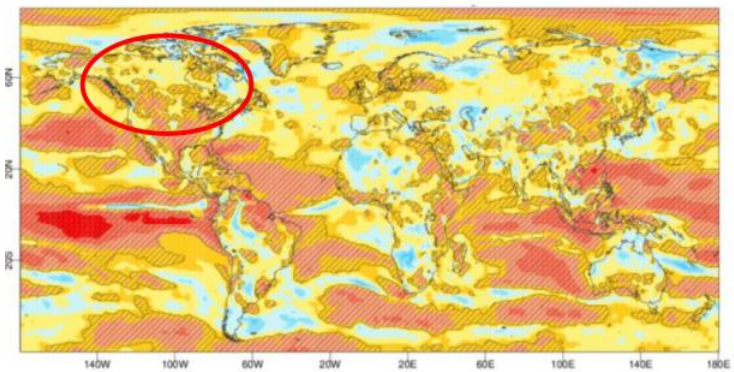
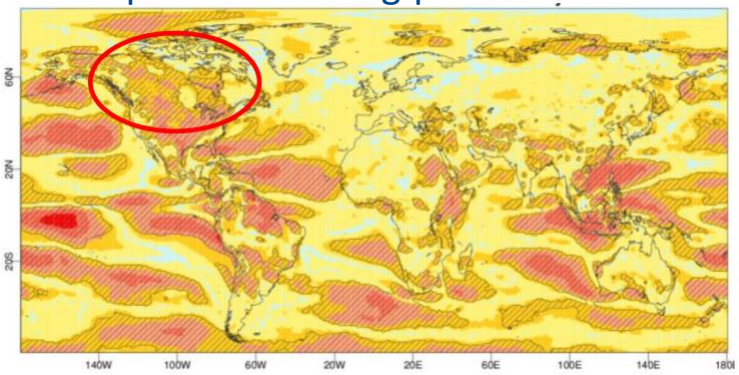
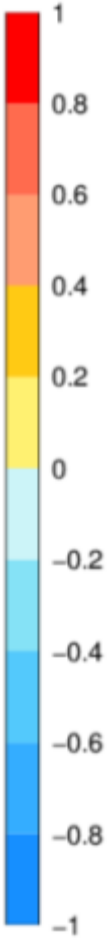
ECMWF S4 10-metre wind speed forecasts for DJF corrected with the predicted Niño3.4 index on a regression estimated using ERA-Interim.

Correlation of the ECMWF S4 ensemble-mean prediction (1981-2015)

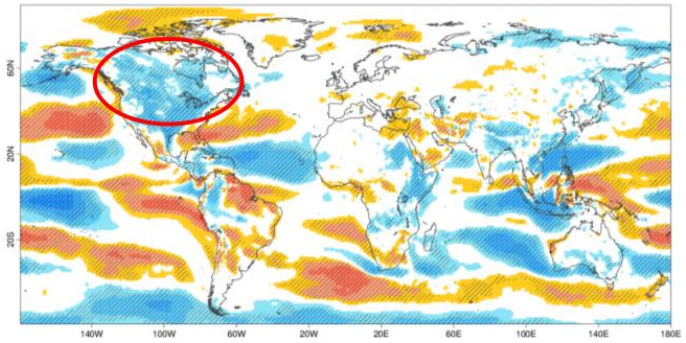


Correlation of the ECMWF S4 ensemble-mean prediction using predicted Niño3.4

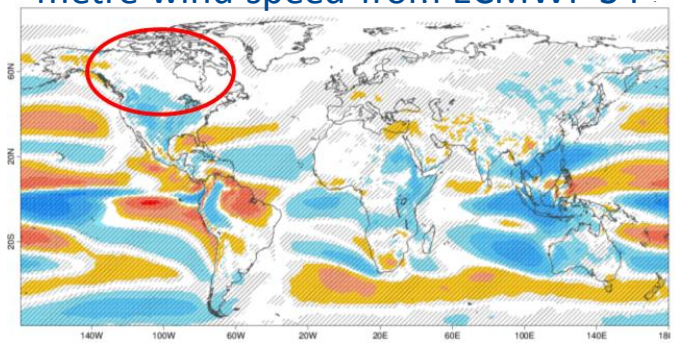


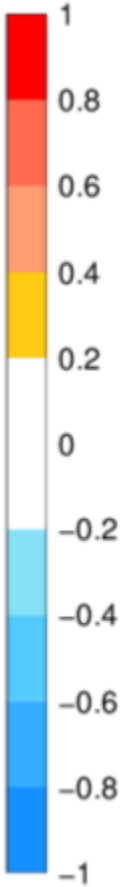


Point correlation of Niño3.4 and 10-metre wind speed from ERA Interim



Point correlation of Niño3.4 and 10-metre wind speed from ECMWF S4

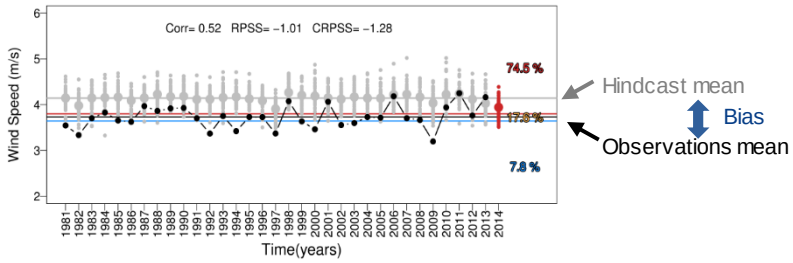


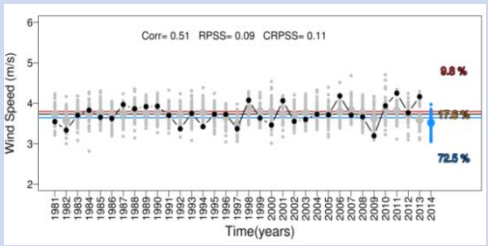
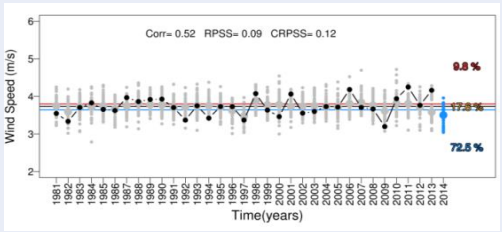
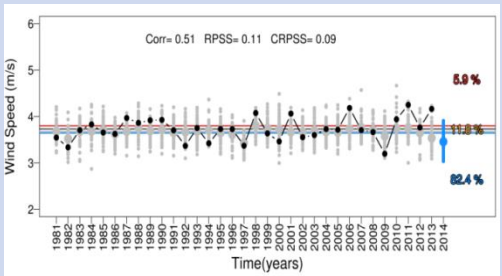


González et al. (in prep.)

Bias adjustment

Raw data



Method	Equation	Description	Result
Simple bias correction	$y_{j,i} = (x_{ij} - \bar{x})\frac{\sigma_{ref}}{\sigma e} - \bar{o}$	Based on the assumption that both the reference and forecasted distribution are well approximated by a Gaussian distribution.	
Calibration method	$y_{j,i} = \alpha x_i + \beta z_{ij}$	Variance inflation modifies the predictions to have the same interannual variance as the reference dataset and corrects the ensemble spread to improve the reliability.	
Quantile mapping	$y_{j,i} = (ecdf^{ref})^{-1} ecdf^{mod}(x_{ij})$	It determines for each forecast to which quantile of the forecast climatology it corresponds, and then they are mapped to the corresponding quantile of the observational climatology.	

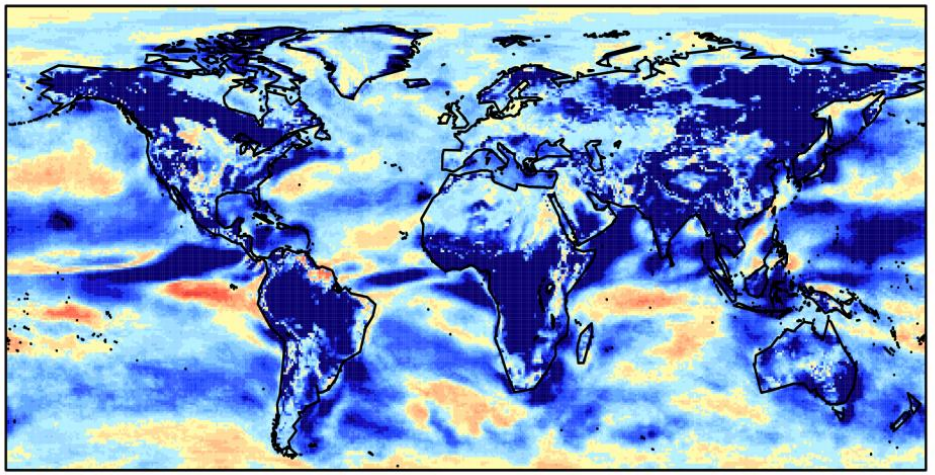
Impact of bias adjustment

Ranked Probability Skill Score

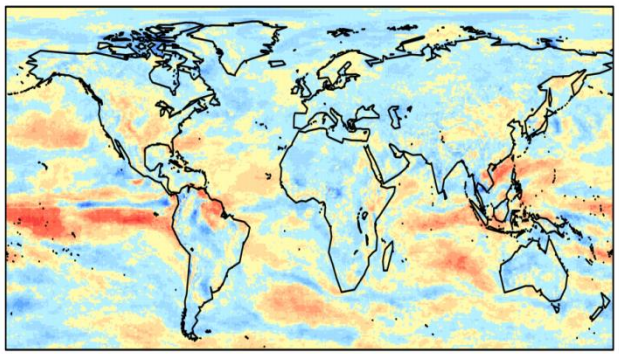
$$RPS = \frac{1}{M-1}\sum_{m=1}^{M}\left[\left(\sum_{k=1}^{m} p_k\right) - \left(\sum_{k=1}^{m} o_k\right)\right]^2$$

$$RPSS = \frac{\overline{RPS} - \overline{RPS}_{reference}}{0 - \overline{RPS}_{reference}} = 1 - \frac{\overline{RPS}}{\overline{RPS}_{reference}}$$

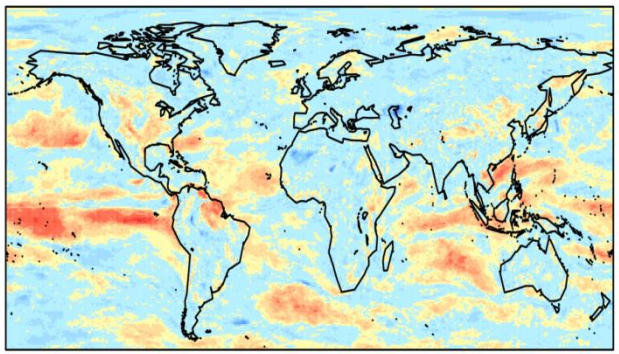
Uncorrected



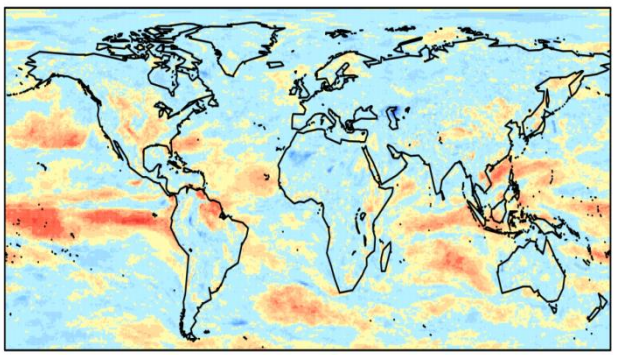
Simple

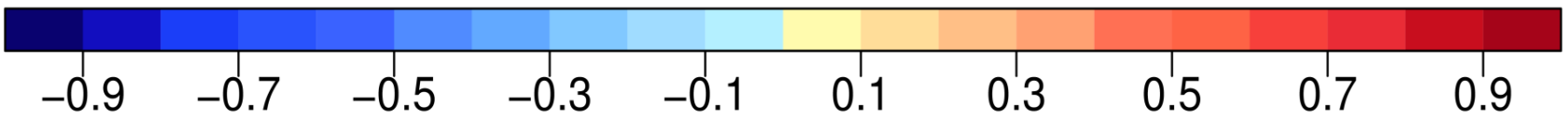


Calibration



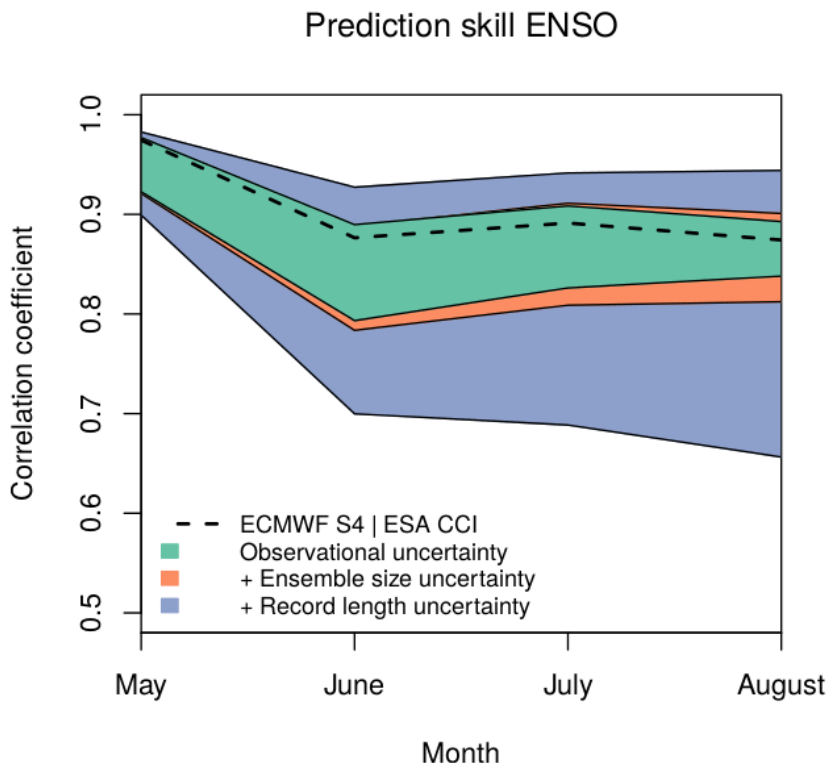
Q-Q mapping

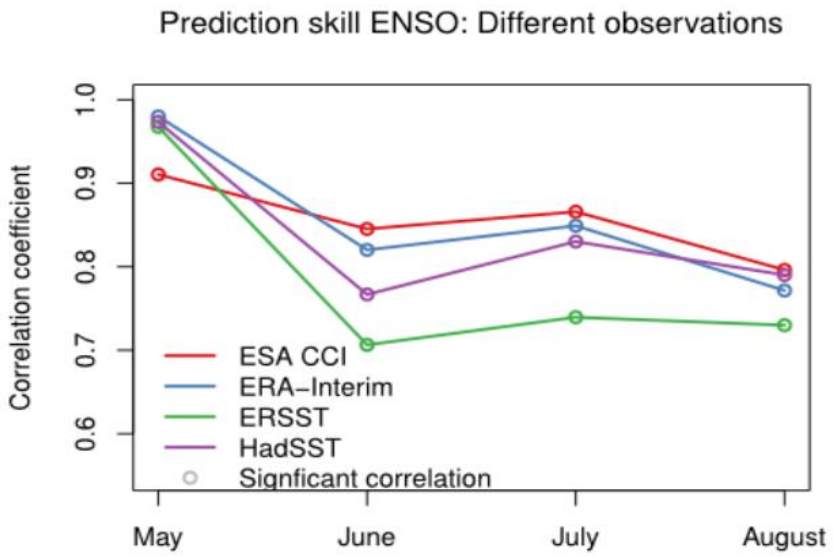




Sources of skill uncertainty

Niño 3.4 SST correlation of the ensemble mean for (right) EC-Earth3.1 (T511/ORCA025) predictions with ERAInt and GLORYS2v1 ics, and BSC sea-ice reconstruction and (left) ECMWF System 4, both started every May over 1993-2009.





Bellprat et al. (2017, Rem. Sens. Env.)

Model and reference uncertainty

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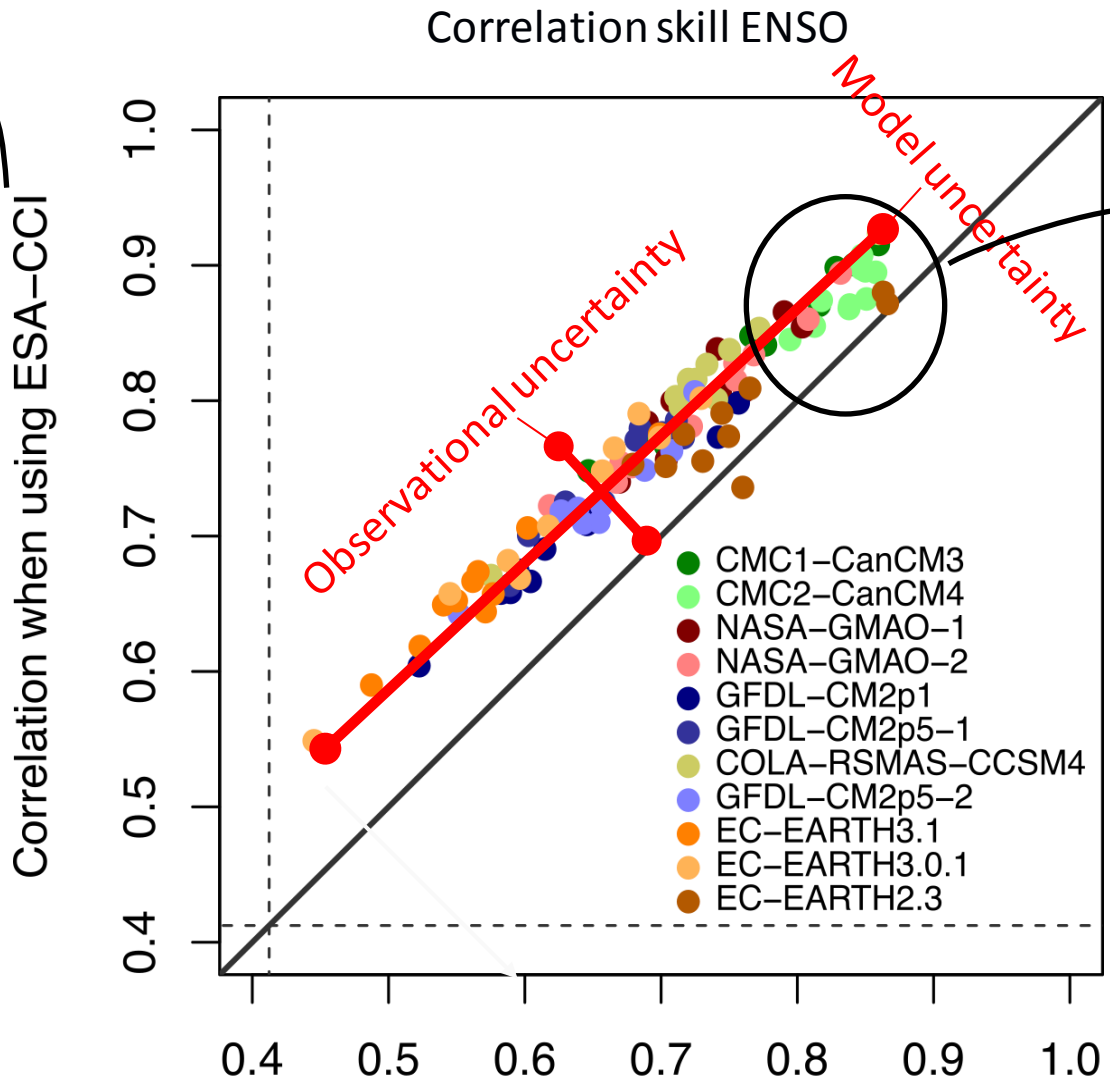
Models can also be used to estimate the quality of observational estimates.

Independent from the models



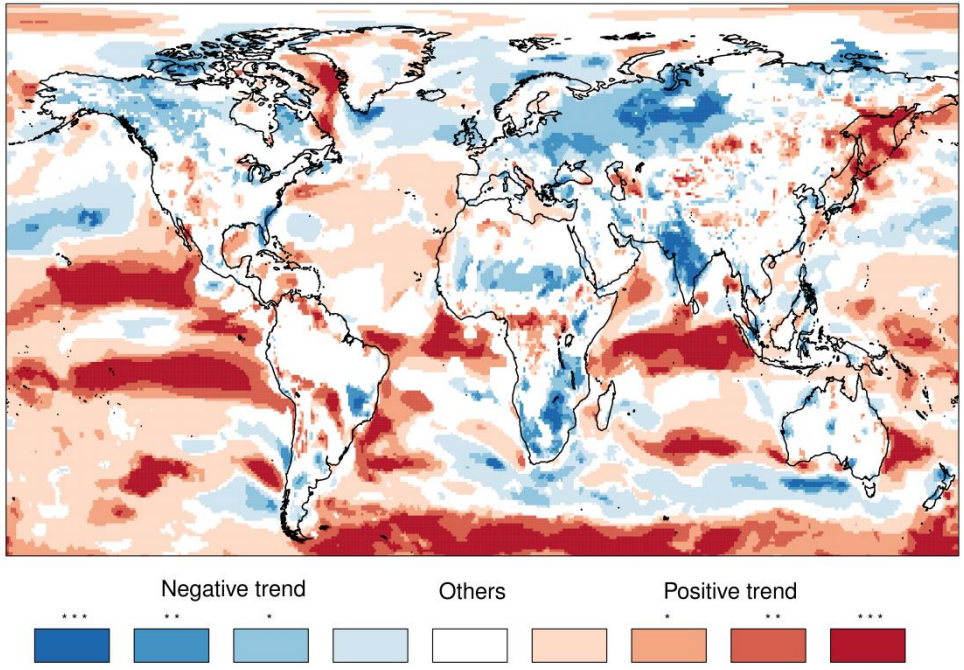
How important for individual systems?

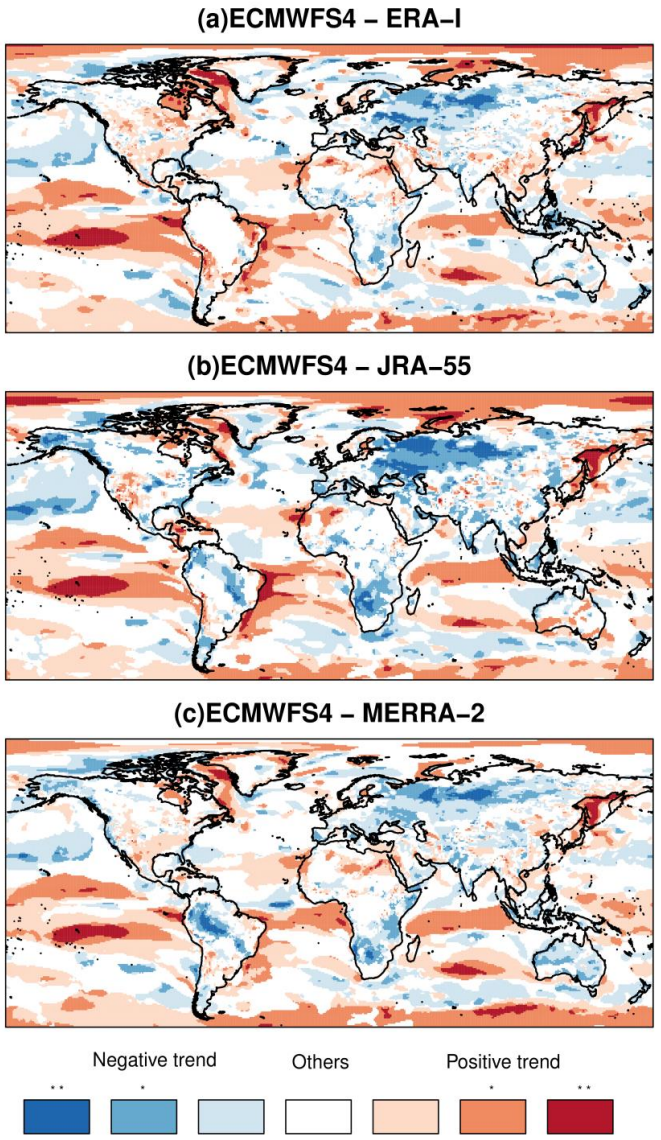
Massonnet et al. (2016, Science)

Reference uncertainty: trends

(Bottom) Coherence of the 10-metre wind speed trends in three reanalyses (ERA-Interim, JRA-55 and MERRA) over 1981-2015 during boreal winter.

(Right) Coherence of the trends between ECMWF S4 and the three reanalyses.





Torralba et al. (2017, ERL)

Improving diagnostics efficiency

- **Computing performance is key**: (left) scalability of a ROC area estimate using loadeR, SpecsVerification and easyVerification.
- An RDF-based approach aiming at the reproducibility of objects (NetCDF file, image) with human and machine-readable solution using a semantic metadata model has been created in QA4Seas.